

NONLINEAR PROCESSING OF AUDITORY BRAINSTEM RESPONSE

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Abstract: - Auditory brainstem response potentials (ABR) are signals calculated from the EEG signals registered as responses to an acoustic activation of the auditory system. The ABR signals provide an objective, diagnostic method, widely applied in examinations of hearing organs. The shape of the time-dependent signal, and its possible distortion, and particularly the presence or absence of characteristic waves are of great diagnostic importance. In the present work methods of automated identification of wave V are presented, using the multilayer perceptron type networks. Classification methods are also proposed, based on cascade architecture of the neural networks used for recognition of the context information.

Keywords: - Auditory brainstem response potentials, neural networks, context classification, nonlinear processing

the person carrying out the ABR examination, and are continuously taking place in the brain of the examined patient.

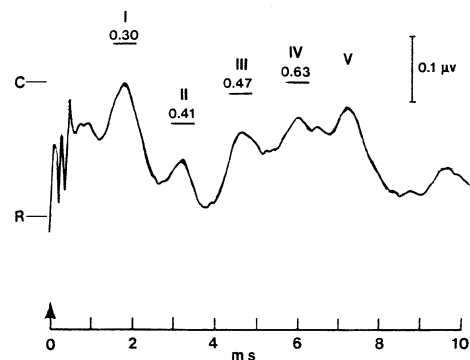


Fig. 1. Typical, regular signal of the ABR

I. INTRODUCTION

The analysis and recognition of auditory brainstem response (ABR) signals is a medical problem of great importance, because at present it is the best known technique of the auditory organs evaluation, providing a truly objective way to determine what is the actual level of sound perception for a given patient. The methods based on recognition of ABR signals do not require the patient's cooperation, what is essential in hearing examinations of little children, persons who do not exhibit any conscious communication with their environment, and persons who intentionally refuse any cooperation with the examining audiologist (e.g. persons simulating hearing loss). However the task of construction of fully automatic method of ABR recognition seems to present considerable technical difficulties. It is because the signals are in general hardly readable, and in particular the evaluation of data part obtained for low intensities of the audio stimulus is especially difficult. The shapes of the ABR recordings obtained for various patients can be considerably different, and even in consecutive studies of ABR signals for the same patient certain differences are observed, because in spite of application of highly sophisticated signal revealing techniques (in studies presented here the synchronic averaging techniques have been mainly applied) the ABR signals are highly distorted by influence of various interference signals, in particular heterogeneous biopotentials.

Particularly difficult is the elimination of influence of other EEG signals (i.e. not invoked by the acoustic stimulus), being the results of other processes, which are not under control of

The above mentioned difficulties particularly concentrate in that part of the study which regards the border zone between hearing and lack of hearing (between presence and absence of hearing), and which is of particular interest for the examining physician. It follows from the fact that in the course of presentation of lower and lower acoustic signals to the patient the fluctuations and deformations of the ABR signals resulting from presence of external signals intensify, introduce considerable difficulties to the process of proper signal interpretation and its automated recognition.

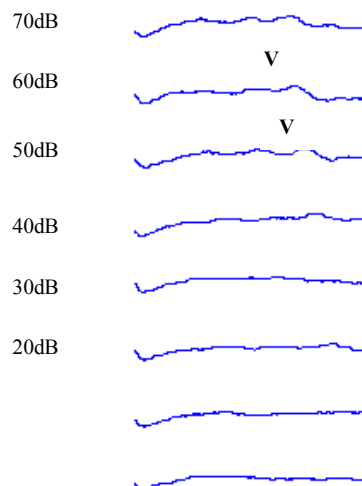


Fig. 2. The recorded, noisy signals of the auditory brainstem response

Report Documentation Page

Report Date 25 Oct 2001	Report Type N/A	Dates Covered (from... to) -
Title and Subtitle Nonlinear Processing of Auditory Brainstem Response		Contract Number
		Grant Number
		Program Element Number
Author(s)		Project Number
		Task Number
		Work Unit Number
Performing Organization Name(s) and Address(es) Department of Automatics AGH Univesity of Technology Krakov, Poland		Performing Organization Report Number
Sponsoring/Monitoring Agency Name(s) and Address(es) US Army Research, Development & Standardization Group (UK) PSC 802 Box 15 FPO AE 09499-1500		Sponsor/Monitor's Acronym(s)
		Sponsor/Monitor's Report Number(s)
Distribution/Availability Statement Approved for public release, distribution unlimited		
Supplementary Notes Papers from 23rd Annual International Conference of the IEEE Engineering in Medicine and Biology Society, October 25-28, 2001, held in Istanbul, Turkey. See also ADM001351 for entire conference on cd-rom. , The original document contains color images.		
Abstract		
Subject Terms		
Report Classification unclassified	Classification of this page unclassified	
Classification of Abstract unclassified	Limitation of Abstract UU	
Number of Pages 4		

This is also the reason that makes the problem of automated ABR signal recognition more interesting from the scientific point of view, because a similar task of revealing and interpretation of subliminal signals (i.e. objectively placed below the noise level) is encountered in many tasks of biomedical engineering and in many other fields (e.g. in geophysics). Therefore it can be assumed that the methods of analysis and recognition of ABR signals can be of some interest to other investigators, not necessarily directly interested in audiology, but trying to cope with the difficulties of interpretation and recognition of totally different signals.

II. PREPROCESSING OF THE ABR SIGNALS

The data concerning the acquisition techniques for the ABR potentials analysed in the present work have been as follows: the patient have been applied an acoustic stimulus in the form of a cracking noise of the intensity between 70 and 20 dB, and next from the EEG signal the ABR signal has been extracted (by the synchronous averaging technique).

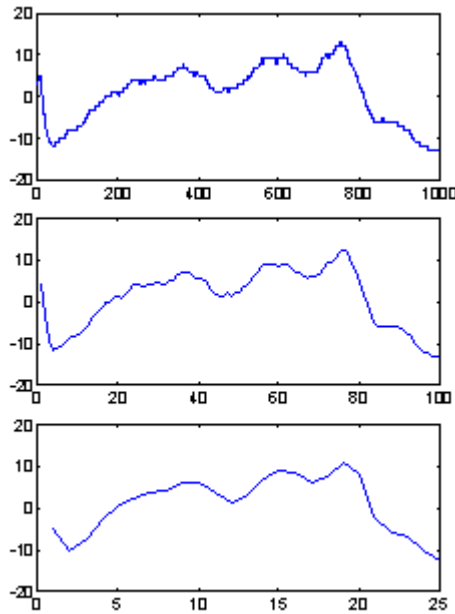


Fig. 3. An exemplary, original ABR signal (1000 points) and the signal after size reduction to 100 and 25 points.

The original size of the ABR signals included 1000 values (covering about 10ms of the response signal). Such a signal may contain many high-frequency, irrelevant components of the EEG signals. Therefore studies have been initiated on using for classification signals of the size reduced to 100 and 25 values, by applying the averaging methods. For the latter case, when the reduction of data contained in the signal was quite considerable, the averaging intervals partly overlapped, in order to preserve the potentially essential information located at the borders of the intervals (averaging intervals of 50 points and 40 point steps have been used).

In Table 1 several best results are shown, obtained for classification of signals 1000, 100 and 25 points in size. During analysis of the above data it can be noticed, that the reduction of the signals size, even so substantial as in the 25 points case, does not lead to loss of essential information contained in the signal (Fig.3). The results obtained for signals of reduced size are better than the results obtained for the original signal.

No.	Neural network architecture	No of epochs	RMS error	Accuracy of the classification [%]	
				Learning set	Test set
1	$1000 \times 12 \times 1$	260	0,63	100	83.12
2	$1000 \times 7 \times 2 \times 1$	325	3,70	92.11	85,71
3	$100 \times 8 \times 1$	479	0,09	100	85,71
4	$100 \times 7 \times 2 \times 1$	414	2,00	97.37	85,71
5	$25 \times 7 \times 1$	310	1,25	98.68	83,01
6	$25 \times 7 \times 1$	288	2,01	96.05	82,31

Table 1. Results obtained for classification of signals 1000, 100 and 25 points in size.

Another transformation applied to the ABR signals was the 100-1100Hz band filtering. The low-pass filter was supposed to reduce the high-frequency EEG components (noise), while the high-pass filter was used to eliminate the low frequency components (trend). The last transform applied was the calculation of the signal's derivative. The transformations did not however result in improvement of the later classification, what can be a proof, that during the transformations some information, essential for the functioning of neural networks, has been removed.

III. THE RESEARCH FOUNDITIONS

The studies of authors of the present work, described in previous publications, have shown that automated recognition of automated brainstem response (ABR) signals is possible. For majority of typical signals the automatic system correctly interpreted the obtained ABR recordings, in particular correctly pointing out the threshold signal intensity, below which the patient was not able to hear the presented acoustic stimulus. It was also confirmed, in accordance with earlier findings, that the problem of resolution between ABR signals invoked by an audible sound signal and ABR found in absence of auditory perception can be reduced to the detection of presence (or absence) of the so called "wave V" in the signal structure.

Particularly this wave, clearly present in ABR signals evoked by strong acoustic stimuli, disappears, decreases, shifts and deforms with the decreasing intensity of the acoustic signal stimulating the response, and finally vanishes in random fluctuation of the ABR signals in the region where patient's

ability to hear the signal is lost. Therefore in all further studies the morphology of the total ABR signal has been ignored, and the attention has been focused on distinguishing between presence and absence of wave V.

IV. THE CONTEXT CLASSIFICATION

In the authors' publications mentioned before it was shown, that the artificial intelligence methods confirm their utility in accomplishing the task of ABR signals classification. Comparing various methods of pattern recognition it has been also found that neural networks are clearly superior to other methods originating from other pattern recognition techniques, therefore in all further studies only neural networks have been applied, without returning to other methods, namely probabilistic or k-means. It has been found that the dominance of the neural model over the other recognition techniques follows mostly from the fact that in the course of recognition neural network (and particularly multilayer network) employs a strongly nonlinear method of the input signal processing. As a result of that nonlinear processing the structure of the studied ABR signal is represented in the internal layers of the network by features being highly nonlinear derivatives of the signal's morphological features. Such a complex form of the signal nonlinear analysis and transformation cannot be built into the structure of other pattern recognition methods, because the form of the required ABR signal transformation (as a proposed mathematical formula) would have to be specified "a priori" and no one knows "a priori" what transformation will be the most effective in revealing the signal's features essential for its recognition at the same time eliminating random deformations. In the neural network the form of nonlinear signal transformation is produced automatically, and in addition it is being adjusted (during the network's learning process) to the properties of the analyzed signal and the chosen[selected] classification criteria. Due to such an approach the decision produced at the network's output can be considerably better and more appropriately adjusted to the specific features of the ABR signal than the decisions worked out by other algorithms of automated pattern recognition.

As mentioned before in the earlier studies the effect of proper classification of ABR signals have been already achieved by a properly chosen neural network (of MRP class), however the problem of quality and reliability of that recognition has emerged. The recognition quality achieved by automated signal analysis (using neural networks) reached only 80% of correct recognitions, while experienced physicians were able to classify the same ABR signals with reliability exceeding 90% (though never reaching 100%). Many attempts have been made to improve the quality of automated recognition, by changing the structure of the neural network used for recognition, optimizing the learning methods, applying many forms of preliminary ABR signal processing before feeding it to the network's input etc. In spite of carrying out very many trials the results of automated recognition were still

considerably inferior to the results achieved by physicians.

A working hypothesis has been proposed, stating that the advantage of the visual evaluation by an excellent specialist over the evaluation carried out by an automated system follows from the fact that the automated system is always restricted to the analysis of shape of a single ABR signals, while the experienced physician acts in a context way. In fact, a human evaluating the shape of ABR signal for a given fixed value of intensity of the stimulating sound signal, has also in mind the shapes of ABR signals for higher and lower signal intensities.

The hypothesis about the utility of context in the recognition process has been confirmed in experiments, in which the physicians tried to resolve the presence or absence of the wave V by looking only at a single ABR signal. The quality of the decisions made by people in such circumstances has decreased considerably and was not considerably better from the quality of recognition obtained in an automated way.

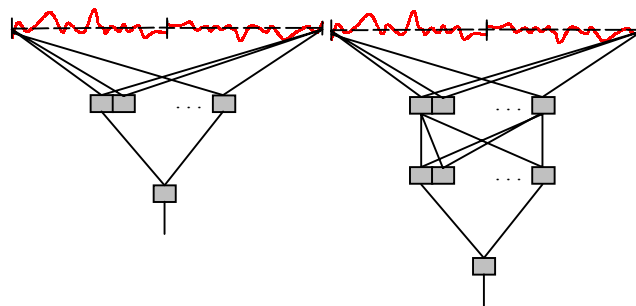


Fig. 4. The double and triple layer neural networks, in which the neurons are connected according to the "every with each other", doublets of signals are fed to the network's input

Figure 4 shows the architectures of the best neural networks using in experiments.

V. SUMMARY

The proven positive effect of context in the performance of people interpreting ABR signals has resulted in undertaking many studies connected with attempts of making use of the context (or other signals, different from the one being recognized at the moment) in the automated recognition of the acoustic brainstem response signals. Thus the problem of ABR signals classification has been moved from the field of one-dimensional signals analysis to the field of multidimensional signals. There are however two multidimensional interpretations of ABR possible. In the first each of the analyzed signals can be considered as an additional dimension, what leads to the space of many dimensions, but relatively simple structure. In the second approach the time dependence of ABR signals obtained for consecutive (decreasing) values of the amplitude of the stimulating signal can be treated as one, two dimensional data structure. In the latter, in general more favorable, case the dimensions determining the variation of ABR signal are

respectively the time since application of the stimulating signal and its amplitude.

The necessity of transition from one- to multidimensional signal interpretation in the ABR signal recognition, while retaining the assumption about application nonlinear transformations (particularly generated by the neural network) in the recognition process is directly related to the problem of dimensionality of these networks. In an obvious way neural network to the input of which a multidimensional signal is being fed, must have more input elements than an equivalent network recognizing one-dimensional signal. It also results in the growth (much stronger) of the number of connections present in such a network between the input elements and the elements in the hidden layers. As it is known the increase in the number of those connections (and the related weight coefficients) leads in turn to the difficulties in realization of the network's learning[training] process. In particular when a limited (with respect to the number of elements) learning set is used and the network's memory capacity is increased (by increasing the number of weight coefficients adjusted during the learning process) one has to be ready for deterioration of the network's properties with respect to the generalization abilities.

The table 2 below shows the new results for the study of recognition of the ABR signals making use of the context signals.

Neural network architecture	No of epochs	RMS Error	Accuracy of the classification [%]	
			Learning set	Test set
$200 \times 10 \times 1$	330	1.98	96,05	87,01
$200 \times 8 \times 1$	395	1.24	96,05	89,61
$200 \times 8 \times 1$	365	1.43	97,37	88,31
$200 \times 7 \times 2 \times 1$	1049	3.94	94,74	85,71

Table 2. Selected best results of the classification for the networks presented in Fig. 4.

That phenomenon has been discovered and described by the present authors in their initial works, oriented towards making use of the nearest context (only one neighboring signal) in the analysis of the ABR signal. At present when the work is directed towards spreading out the context to greater numbers of the ABR signals considered at the same time, the intensification of difficulties should be expected, expressed mainly by instantaneous learning of the network during the presentation of the learning sets and very poor results during testing of its performance using the test sets. In order to overcome this difficulty studies have been undertaken concerning situations when not the whole multidimensional ABR signal is being fed to the network's input, but only its selected features are presented, related to the general picture of the studied signal dependence, without the excessive unessential details. The formal similarity between the

structure of the multidimensional ABR signal and the dynamic speech signal multispectra and the need for focusing the analysis on the envelope of the signal observed in both cases (for the ABR signal it is the above mentioned wave V, while in speech signal the so called formants) suggest a presumption, that certain techniques applied in the speech signal analysis (e.g. the LPC models) can be also useful in the recognition of ABR signals.

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This paper was supported by AGH grant 10.10.120.39